International Journal of Engineering Research in Africa
ISSN: 1663-4144, Vol. 52, pp 62-72

Submitted: 2019-06-23
Revised: 2020-09-13
Accepted: 2020-10-09
Online: 2021-01-14

Fusion of High-Resolution SAR and Optical Imageries Based on a Wavelet Transform and IHS Integrated Algorithm

Abdelrahman Yehia[1,a], Mohamed Safy[2,b] and Ahmed S. Amein[3,c*]

[1]Radar Dept., EEE. Military Technical College, Cairo, Egypt

[2]Department of Electrical Engineering, Egyptian Academy for Engineering & Advanced Technology, Egypt, Cairo, Egypt

[3]October 6, University, Cairo, Egypt

[a]a.yehia@mtc,edu.eg, [b]msafy@eaeat.edu.eg, [c]asamein@mtc.edu.eg

Keywords: SAR; optical, image fusion, wavelet, IHS

Abstract. Multi-sensor remote sensing data can significantly improve the interpretation and usage of large volume data sources. A combination of satellite Synthetic Aperture Radar (SAR) data and optical sensors enables the use of complementary features of the same image. In this paper, SAR data is injected into optical image using a combining fusion method based on the integration of wavelet Transform and IHS (Intensity, Hue, and Saturation) transform. Not only to preserve the spectral information of the original (MS) image, but also to maintain the spatial content of the high-resolution SAR image. Two data sets are used to evaluate the proposed fusion algorithm: one of them is Pleiades, Turkey and the other one is Boulder, Colorado, USA. The different fused outputs are compared using different image quality indices. Visual and statistical assessment of the fused outputs displays that the proposed approach has an effective translation from SAR to the optical image. Hence, enhances the SAR image interpretability.

1. Introduction

Over the past decade, the fusion process that combine a complementary information from multi-source of data into a single resultant image such as optical remote sensing (RS) data as a passive sensor image or a very high spatial resolution microwave data as an active one has a number of additional benefits. This different data from platforms has become increasingly available to extract the urban features and land cover information from such data. It is well known that optical sensors can provide information about the reflective characteristics of features of the Earth surface, while the synthetic aperture radar (SAR) data measures the physical properties of texture and information on the surface roughness [1]. They can operate all day and night in all weather conditions unlike the optical sensors. Also, SAR sensor can acquire images that independent of the conditions of illumination [2]. However, SAR images of complex scenes such as urban areas cannot be visually interpreted in an accurate manner due to some radar imaging effects like the multiple-bounce propagation and speckle noise phenomenon that leads to imprecise object borders [3]. On the other hand, Optical images are much easier to interpret by human operators which represent the reflectance of solar energy from objects in a target area; therefore, they usually provide more details at similar resolution [4]. Therefore, it is desirable for many tasks to create a fused product by merging high spatial resolution SAR with moderate spatial resolution MS images to better understanding of the objects in target areas [5-6].

The motivation behind data fusion is to generate an interpretation of the scene not obtainable with data from a single sensor, or to form a composite image whose quality is superior to any of the individual input images [7]. Panchromatic image has a high spatial resolution gives geometric details of a data and multispectral image provides the visual performance by combining the characteristics of the optical sensors to integrate the multiple images into a resultant image that is more suitable for the human visual purpose or computer processing applications [8-9].

Multi-sensor remote sensing pixel level data fusion approaches have been discussed in several studies. Generally, these methods can be classified among two categories: component substitution (CS) which is considered as a spatial domain fusion method and multi-resolution analysis (MRA) as a Transform domain fusion method. The CS approach is based on projecting the MS image into another space and replacing one component of MS image with the high spatial PAN image [5]. Due to the spectral distortion of CS methods, Multi-scale decomposition (MSD) approach has been performed. The MRA methods include Laplacian pyramid and the wavelet transform are based on MSD of the high spatial resolution imagery to extract the spatial details and then transferring into the color image. Graphically, the entire multi-scale representation looks like a pyramid (pyramid decomposition), with the original image on the bottom and smaller images from every cycle stacked one on another. The Pyramid-based image fusion methods, including Laplacian pyramid transform, were all developed from Gaussian pyramid transform which has been modified and widely used in a number of image processing applications including the image fusion [10] [11]. Particularly, The MRA fusion approaches usually to provide superior performance in terms of reducing the spectral distortion compared to CS or spatial domain based methods [12] [13].

On the other hand PCA transformation can acquire higher spatial resolution but provides more serious distortion of spectral characteristics. Pyramid based fusion not produces spectral degradation but its performance reduces with decomposition level. On the other hand, Wavelet transform based fusion method provides high SNR as well as no spectral degradation for fused images but suffers from directional selectivity during fusion. The A`trous wavelet transformation can preserve the spatial data while it lacks a high spatial resolution in the results. Hybrid methods use the advantages of both the CS and MRA methods with a combination of them [14]. Metwalli et al. [15] studied hybrid fusion method based on PCA and high pass filter (HPF) for providing pan-sharpened image with superior spatial resolution and less spectral distortion. It is found that the developed method is significantly reduced the spectral distortion compared with the PCA, HPF, and Gram-Schmidt (GS) fusion methods.

This article aims to inject the spatial information of the SAR image into the optical image, while maintaining its spectral properties and obtaining an easy interpretable SAR features. An integrated IHS and wavelet fusion approach is presented to make full use of the merits of the IHS and wavelet transform fusion methods.

2. Wavelet Transform and IHS

Generally, Wavelet transformation (WT) is a mathematical tool for signal processing, has now been widely used in the optical image fusion domain, i.e., fusing high spatial resolution PAN images with high spectral resolution MS images. Many image fusion methods based on wavelet transformation have been investigated. Base on multi-scale decomposition (MSD), Discrete Wavelet Transform (DWT) can decompose a high spatial resolution PAN image into high frequency and low frequency coefficients. The high frequency component from PAN can then be injected into the low spatial resolution MS image, resulting in a PAN-sharpened MS image with high spatial details which is generated by implementing an inverse discrete wavelet transform (IDWT). This basis could be adopted for the fusion between different sources of images such as SAR and optical images [6]. A stand-alone wavelet image fusion method can well retain the color information of the MS image, but with visible artifacts in the fusion results [16].

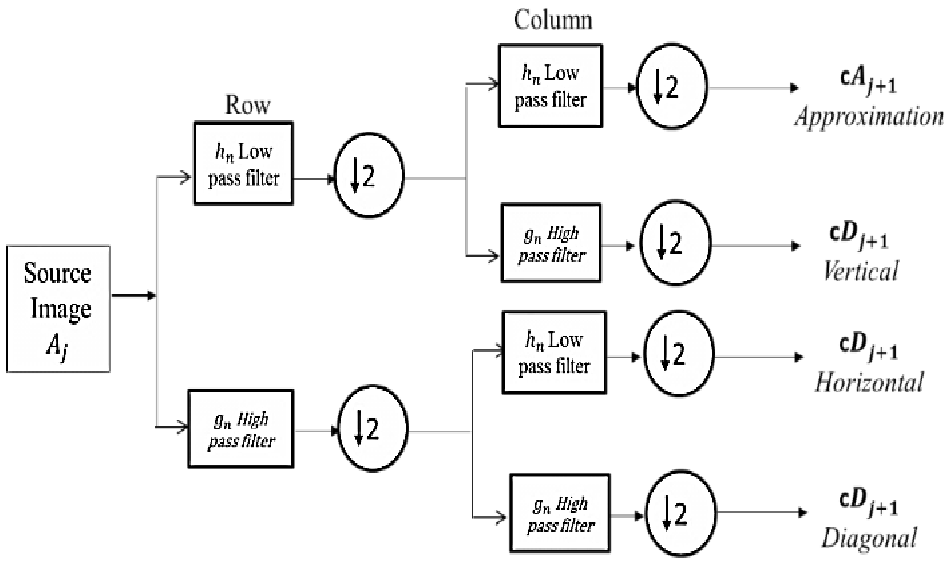

Figure 1. 2-D DWT: The input image is decomposed in rows and columns by using low-pass (h_n) and high-pass (g_n) filters and subsequent down sampling at each level to get approximation and details coefficients [17].

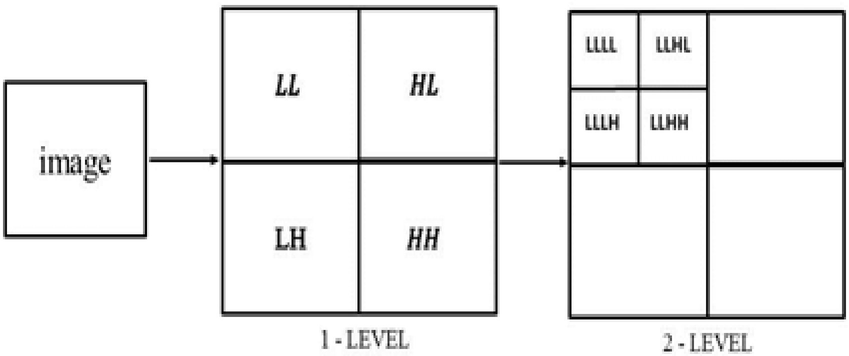

Figure 2. Multi-level Stationary wavelets transform.

The (intensity–hue–saturation) IHS fusion method falls under spatial domain techniques that can preserve the spatial characteristics of the high spatial resolution image, but causes a kind of color distortion depends on the correspondence between the high spatial resolution image and the intensity component of the low spatial resolution MS image (SAR image is considerably different from the intensity image of a MS image; thus, it usually causes significant color distortion) [18]. The integration of wavelet and IHS methods could utilize the merits of individual methods and avoid the drawbacks of the methods [6].
The R, G and B bands of the MS image are separated then transformed into HIS color space, the intensity (I), hue (H) and saturation (S), by forward IHS transform. Before replacing the I component with PAN image, we match the histogram of the PAN image to the histogram of I component to reduce the color distortion. Performing the inverse transformation to obtain a high spatial resolution MS image, but the fusion image suffers a serious spectral distortion. The main steps are illustrated in Fig. 3, of the standard IHS fusion scheme [19-20].

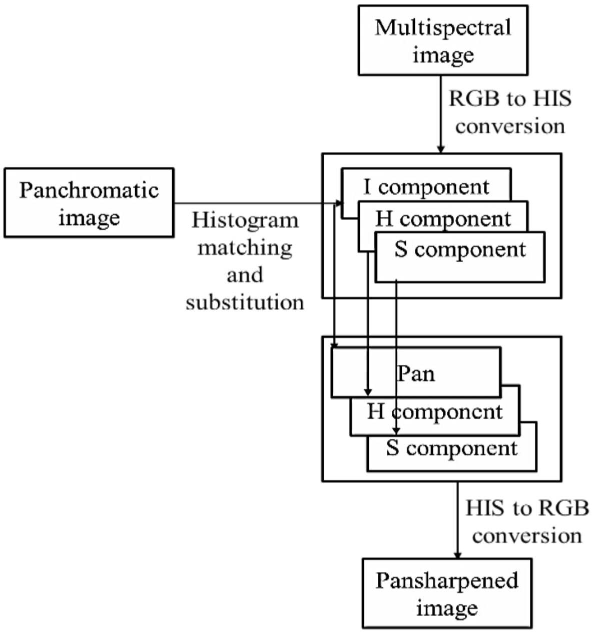

Figure 3. Image Fusion with the IHS method.

3. Methodology

This study aims to inject the spatial information of the SAR image into the optical image, while maintaining its spectral properties and obtaining an easy interpretable SAR features. An integrated IHS and wavelet fusion approach is presented to make full use of the merits of the IHS and wavelet transform fusion methods. The followed flowchart of the proposed method is illustrated in Fig 4.

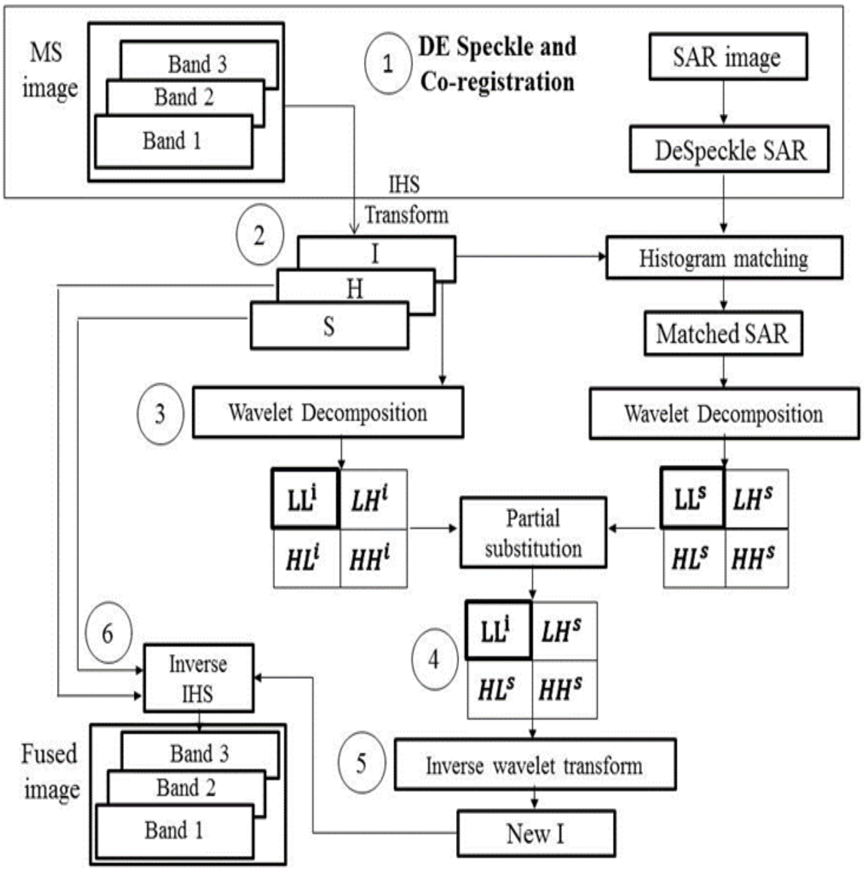

Figure 4. Flowchart of the SAR-Optical proposed image fusion algorithm.

Generally, the IHS transform is utilized to combine the color information of the optical image with the spatial detail of SAR image. The wavelet transform is implemented to extract spatial detail from SAR image and produce a new intensity image.

3.1. Data Preprocessing

3.1.1. Co-Registration of Optical and SAR Images

Image-to-image registration refers to the process of aligning images so that their details overlap to correct the nonlinear geometrical differences between the two images. It is achieved by rotating and/or translating the test image to align with the reference image, which is a crucial step, so it is an important part to match them geometrically. However, image matching and data co-registration, such as optical and SAR imagery, considered as a challenge in remote sensing data fusion, it is still an open field of research for many years [21]. In our algorithm, the SAR image is regarded as a reference image and the optical image is the test one. It is achieved by automatically finding the affine transformation which maps a point set from reference image into the same corresponding points in the other image.

3.1.2. Speckle Reduction of the TerraSAR Image

Removal of the Speckle noise is a substantial step in further studies. The analysis of the microwave images must be based on the speckle effects suppression techniques such as local region, gamma map, and lee-sigma filters [22-6]. In general, speckle in SAR images is supposed to be modeled as multiplicative noise, which can be reduced by multi-look processing or spatial filtering. Here, the enhanced Lee filter was selected, such that the filtered image could preserve the inherent characteristics of the SAR image while minimizing speckle noise [23].

3.2 Image Fusion Algorithm

A set of experiments that have been carried out on the different datasets are described in the following subsection.

// This program to Fused of High-Resolution SAR and Optical Imageries Based on a Wavelet transform and IHS Integrated Algorithm

1. Read SAR image in img1
2. Read MSI image in img2
3. Image Co_registration between img1 and img2

// Noise reduction of SAR image

4. Despeckle img1
5. Read Red, green and blue components as R, G, B

// RGB to IHS conversion

6. Calculate Num = (R-G)+(R-B)
7. Calculate Dum = sqrt((R-G).^2+(R-B).*(G-B)
8. Th = acos 0.5 ((Num/ Dum)+eps)
9. H Component = Th/(2*pi)
10. Calculate NUS = min(min(R,G),B)
11. Calculate DUS = (R+G+B+eps)
12. S Component = 1-3.*NUS/DUS
13. I Component = =(R+G+B)/3

// Histogram matching between pan and intensity

14. img1_new = histogram matching between img1 and I component

// level2 pan decomposition

15. Extract Approximation_P, horizontal_P, vertical_P and diagonal_P coefficients using 2D Swt filter

// level2 intensity decomposition

16. Extract Approximation_I, horizontal_I, vertical_I and diagonal_I coefficients using 2D Swt filter

// Fused Approximation

17. fused_diagonal component = masking and addition diagonal_P and diagonal_I coefficients
18. fused_horizontal component = masking and addition horizontal_P and horizontal_I coefficients
19. fused_vertical component = masking and addition vertical_P and vertical_I coefficients
20. fused_ approximation component = pixel based mean rule between approximation_P and approximation_I coefficients

// Inverse wavelet transform (reconstruction)

21. New_I = Iswt for fused_diagonal, fused_horizontal, fused_vertical and fused_ approximation components

// IHS TO RGB CONVERSION

22. img2_new = Inverse IHS of New_I and H, S Component

4. Quality Assessment

There are many image fusion approaches have been proposed to efficiently fuse the MS and SAR images and between PAN and MS imageries. However, the quality judgment of the fused image should be assessed in different remote sensing applications [24]. Several indices for assessing the image quality have been proposed so far, which can also be implemented to evaluate the fusion performance in terms of statistical indicators. Image assessment methods can be generally divided into two classes: qualitative (or subjective) methods and quantitative (or objective) methods [25].

In the proposed structure, the performance of the fused image depends on the visual comparison between the fused image and raw input images [24]. A quality indicator that measures spectral and spatial similarity between multispectral and fused images is mainly visual [26]. Peak Signal-to-Noise Ratio, Root Mean Square Error, the spectral correlation coefficient and the Entropy.

5. Results and Discussion

A Pleiades image of 21 May 2018 and a TerraSAR-X image of 27 May 2018 have been used. The Pleiades data have four multispectral bands (B1: 0.45–0.52 mm, B2: 0.52–0.60 mm, B3: 0.63–0.69 mm and B4: 0.76–0.90 mm) and one panchromatic band (Pan: 0.45–0.9 mm). The spatial resolution is 0.5 m for the panchromatic image, while it is 2 m for the multispectral bands. While TerraSAR-X parameters are shown in table 1.

Table 1. The characteristics of the TerraSAR-X data.

POLARIZATION	GROUND RANGE DETECTED (GRD)	FREQUENCY
HH	0.28 M	8-12.5 GHZ

Testing Data with different spatial resolutions are at somewhere urban region from as displayed in Fig. 5 and Fig. 6.

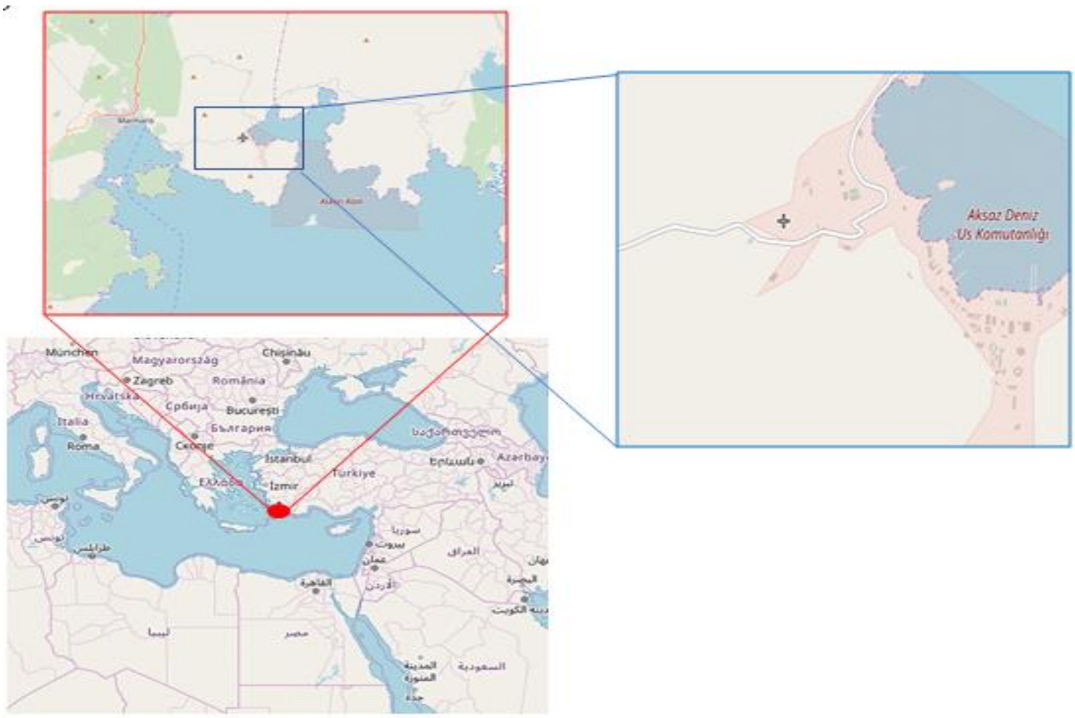

Figure 5. Location of the selected area in Aksaz, Turkey.

(a) (b) (c)

Figure 6. The Original Pleiades and TerraSAR-X images (a) Pan image, (b) MS image (R, G and B), (c) SAR image.

The SAR and panchromatic images were used as a high-resolution sample data in two comparative experiments to verify the transferring of the spatial information and color information to be well fused, spectral and spatial quality metrics were adopted to assess the data fusion quality.

(a) (b)

(c)

(d)

Figure 7. Fusion results between SAR and MS images using different methods
(a) Using DWT. (b) Using IHS. (c) Using DWT-IHS. (d) 2D multi-level SWT.

In Fig. 7. The standalone wavelet fusion method can enhance the spectral information of the fusion result than the original MS data and a severe color distortion exists when compared with HIS fusion method. By using the proposed wavelet-IHS fusion method, the spatial information of the SAR data can be incorporated into the MS images and easily interpreted than those in the original SAR data and also clearer than the original MS image even though the correlations between the SAR and MS images are very low. From the above fusion results, it is easy to see that SWT fusion method preserve the spatial information of the High-resolution SAR image and the spectral information of the original optical image.

According to the image interpretation of the before and after fusion, it can be seen that a building is difficult to identify in all of the MS image because it is represented by only a few pixels; it is also difficult to identify in the SAR image because its appearance is different from that in a traditional optical image we usually see. However, in the fused images of the proposed wavelet-IHS method, roads and buildings can be much easier interpreted because of the integration of spatial and color information.

The statistical comparison of the fusion results can evaluate the performance of each image fusion method in our study which consists of band 1, band 2, and band 3 according to (BGR) spectral bands. Table 2 shows the spectral Quantitative comparison between the fused image bands and the corresponding bands of the original MS image for the stand-alone wavelet, standalone IHS and the proposed wavelet-IHS methods, respectively. In general, the proposed DWT-IHS method is significantly higher than those of the other three methods in terms of Spectral CC and E. The proposed wavelet-IHS fusion result exhibits the lowest values of MSE among three fusion method, which means the less color distortion and the closer to original MS image and generates the highest PSNR values.

Generally, Multi-sensor data are not captured at the same shooting time. After fusing the SAR details into the MS images, the IHS and wavelet results have significantly poorer color information than the proposed method according to Table 3. The spatial CCs between all the fused images with the SAR are much higher than that of the SAR with the original MS image (R band: 0.013; G band: 0.0194; and B band: 0.024); this indicates that the spatial information from SAR has been substantially injected into the MS image after the fusion. Nevertheless, The IHS fusion method and the wavelet fusion method are slightly higher than those by using the proposed wavelet-IHS method as shown in table 2. Overall, the fusion quality of the proposed method is obviously higher than those of the stand-alone IHS and wavelet fusion methods in terms of color preservation and spatial information. Also, In terms of interpretability as well.

Table 2. Quantitative results of different fusion approaches between SAR and MS images.

Method	SAR Spectral CC			PSNR			MSE			E		
	B3	B2	B1	B3	B2	B1	B3	B2	B1	B3	B2	B1
DWT	0.75	0.83	0.8	74.05	75.59	76.86	0.0026	0.0018	0.001	6.77	6.8	6.6
IHS	-0.35	-0.1	0.298	69.31	68.04	66.59	0.0076	0.0102	0.014	6.22	5.58	6.65
IHS-DWT	**0.700**	**0.85**	**0.85**	**76.43**	**75.64**	**74.90**	**0.0015**	**0.0017**	**0.002**	**6.84**	**6.89**	**6.89**
SWT	**0.855**	**0.89**	**0.858**	**89.51**	**91**	**92.39**	**0.00007**	**0.00005**	**0.00003**	**6.828**	**6.69**	**6.42**

Table 3. High frequency component correlation coefficients of different fusion approaches between SAR and MS images.

Method	SAR Spatial CC		
	B3	B2	B1
DWT	0.37	0.51	0.52
IHS	0.6	0.55	0.51
IHS-DWT	**0.5**	**0.46**	**0.433**
SWT	**0.387**	**0.54**	**0.55**

6. Conclusions

This paper proposed a new method to fuse high spatial resolution PAN and SAR images with moderate spatial resolution MS image for smoothing the interpretation of SAR images. The new fusion method is based on the integration of DWT and IHS transform, because the standalone IHS and the wavelet fusion methods do not introduce satisfactory fusion results, especially at SAR and optical fusion, due to significant grey value differences (low CCs) between SAR images and MS images. The integrated wavelet-IHS fusion method utilizes the merit of the IHS fusion in integrating spatial resolution information and the merit of the wavelet fusion in preserving color information.

Visual evaluation presents that the color of the fusion result by the proposed SWT method is much closer to original MS image than other methods. In addition to, the statistical analysis shows that the spectral quality of the fusion results of the proposed SWT method is very well; whereas the color information of the stand-alone HIS, wavelet and the integrated wavelet-IHS fusion results is substantially distorted. In terms of spatial detail, the fusion results by the improved method are higher than to those results obtained by the other individual methods.

From these experiments that the performance of SWT appears to have a superior performance in terms of all of the image quality indexes than other traditional methods. The values of the evaluation parameters also lend support these comments. However, the image fusion based method has some limitations, and it requires a reference optical image covering the same scene with SAR image, As a continuation of this research, we note, from the related work survey, that image fusion continues to be an active and productive area of research.

References

[1] Amarsaikhan, D., et al. "Fusing high-resolution SAR and optical imagery for improved urban land cover study and classification." International Journal of Image and Data Fusion 1.1 (2010): 83-97.

[2] Lopez, Carlos Villamil, Harald Anglberger, and Uwe Stilla. "Fusion of very high-resolution SAR and optical images for the monitoring of urban areas." 2017 Joint Urban Remote Sensing Event (JURSE). IEEE, 2017.

[3] Tao, Junyi, et al. "Interpretation of SAR images in urban areas using simulated optical and radar images." 2011 Joint Urban Remote Sensing Event. IEEE, 2011.

[4] Schmitt, Michael, Florence Tupin, and Xiao Xiang Zhu. "Fusion of SAR and optical remote sensing data—Challenges and recent trends." 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE, 2017.

[5] Zhang, Wenyuan, and Min Xu. "Translate SAR Data into Optical Image Using IHS and Wavelet Transform Integrated Fusion." Journal of the Indian Society of Remote Sensing 47.1 (2019): 125-137.

[6] Hong, Gang, Yun Zhang, and Bryan Mercer. "A wavelet and IHS integration method to fuse high resolution SAR with moderate resolution multispectral images." Photogrammetric Engineering & Remote Sensing 75.10 (2009): 1213-1223.

[7] Kim, Jun-chul, Young-ran Lee, and Sung-hee Kwak. "The fusion of SAR images and optical images based on the use of wavelet transform: to improve classification accuracy." SAR Image Analysis, Modeling, and Techniques VII. Vol. 5980. International Society for Optics and Photonics, 2005.

[8] Liu, Guang, et al. "Multisource remote sensing imagery fusion scheme based on bidimensional empirical mode decomposition (BEMD) and its application to the extraction of bamboo forest." Remote Sensing 9.1 (2016): 19.

[9] Wang, Jianguo, Yunfeng Wang, and Zhisheng You. "SAR and optical images fusion algorithm based on wavelet transform." Fusion 2004: Seventh International Conference on Information Fusion. 2004.

[10] Pradeep, M. "Implementation of image fusion algorithm using MATLAB (LAPLACIAN PYRAMID)." 2013 International Mutli-Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s). IEEE, 2013.

[11] Pajares, Gonzalo, and Jesus Manuel De La Cruz. "A wavelet-based image fusion tutorial." Pattern recognition 37.9 (2004): 1855-1872.

[12] Kahraman, Sevcan, and Alp Ertürk. "Review and Performance Comparison of Pansharpening Algorithms for RASAT Images." Electrica 18.1 (2018): 109-120.

[13] Jinju, Joy, et al. "Spatial frequency discrete wavelet transform image fusion technique for remote sensing applications." Engineering Science and Technology, an International Journal(2019).

[14] Ghassemian, Hassan. "A review of remote sensing image fusion methods." Information Fusion 32 (2016): 75-89.

[15] Metwalli, Mohamed R., et al. "Image fusion based on principal component analysis and high-pass filter." 2009 International Conference on Computer Engineering & Systems. IEEE, 2009.

[16] Aiazzi, B., et al. "MTF-tailored multiscale fusion of high-resolution MS and Pan Imagery." Photogrammetric Engineering & Remote Sensing 72.5 (2006): 591-596.

[17] Gungor, Oguz, and Jie Shan. "Evaluation of satellite image fusion using wavelet transform." proceedings of 20th Congress ISPRS “Geo-Imagery Bridging Continents. 2004.

[18] Švab, Andreja, and Krištof Oštir. "High-resolution image fusion: Methods to preserve spectral and spatial resolution." Photogrammetric Engineering & Remote Sensing 72.5 (2006) : 565-572.

[19] Sruthy, S., Latha Parameswaran, and Ajeesh P. Sasi. "Image fusion technique using DT-CWT." 2013 International Mutli-Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s). IEEE, 2013.

[20] Yadav, Neha, and Shivani Shrivastri. "A review of image fusion using IHS with wavelet transform." International Journal of Computer Science Trends and Technology 2.6 (2014): 15-20.

[21] Schmitt, Michael, Florence Tupin, and Xiao Xiang Zhu. "Fusion of SAR and optical remote sensing data—Challenges and recent trends." 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE, 2017.

[22] Amarsaikhan, D., and T. Douglas*. "Data fusion and multisource image classification." International Journal of Remote Sensing 25.17 (2004): 3529-35

[23] Liu, Guang, et al. "Multisource remote sensing imagery fusion scheme based on bidimensional empirical mode decomposition (BEMD) and its application to the extraction of bamboo forest." Remote Sensing 9.1 (2016): 19.

[24] Macleod, Robb D., and Russell G. Congalton. "A quantitative comparison of change-detection algorithms for monitoring eelgrass from remotely sensed data." Photogrammetric engineering and remote sensing 64.3 (1998): 207-216.

[25] Shi, Wenzhong, et al. "Wavelet-based image fusion and quality assessment." International Journal of Applied Earth Observation and Geoinformation 6.3-4 (2005): 241-251.

[26] Fonseca, Leila, et al. "Image fusion for remote sensing applications." Image fusion and its applications. IntechOpen, 2011.